An Unsupervised Decoding Framework for Prosthetics

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Prostheses have been around for a long time, but finding a good way to control multi-degrees of freedom artificial limbs is still a challenge. Nowadays most artificial limbs are controlled with switchable automatic control mechanisms; however this takes control away from the user, and is complicated to learn and generally unpleasant. In this talk an unsupervised decoding framework is presented that can extract information from neural signals in order to directly use it to control prostheses in a way that is natural and intuitive for the user. In fact, this approach puts the user in the loop as the controller, making it possible to improve learning capabilities via plasticity.

There are two basic types of electrical signals that can be collected from the neuro-muscular system: *Electromyogram* (EMG) and *Electrical Neurogram* (ENG). Of these, the latter is exclusively invasive, while for EMG non invasive technology is also available which is widely used for prosthetic control. However, it is not easy to obtain the *motor unit action potentials* (MUAPs) from EMG. The problem of obtaining MUAPs from EMG can be tackled by improving independent component analysis methods for decomposition.

Once the MUAPs are obtained, the dimensionality of information can be reduced by using *metric learning*. This technique reduces the dimension of data while preserving the metric properties of the input, i.e. projecting (dis)similar neural activity to points close to (away from) each other in the lower dimensional space. Metric learning projects the non informative data to the null space of the low dimensional output, using a cost function that weights the individual single channel metrics. Metric learning can be either supervised or unsupervised. Two variations of this approach are presented here: an *unsupervised* approach that extracts MUAPs trains with Principal Component Analysis (which is the simplest of metric learning), and a *supervised* approach for visualization and data separation in a labeled experiment.

In the first experiment, data was obtained with a high density EMG sensors grid in able volunteers that were performing exion/extension movements. From applying PCA to this data, we can observe that *two* principal components are actually needed to control one antagonistic movement: this is caused by the fact that muscles work only by pulling, so that in order to obtain antagonistic movements we need PCA information from two muscles. In order to get around this issue, application of Complex PCA is introduced. For that purpose, the original EMG channels are divided in two groups, by analyzing the cross correlation between channel firings. These are then paired using a complex vector and fed to the Complex PCA algorithm to extract information on muscle synergies. This way the eigenvalues are still real, but principal components are complex. At the end of this process, only *one single* complex principal component can be used to capture information on the flexion/extension movement.

Another issue with the application of the PCA approach is how to assign the principal components to the motor control space. In fact, while the projected subspace and the hand motor control space are both orthogonal, they are not necessarily aligned. Therefore, we need to appropriately rotate the principal directions to align them with the motors of the biomechanic hand. While there is more than one way to apply a rotation, it can be seen that by using VARIMAX we can obtain a sparse representation of the projection matrix, while leaving the eigenvectors unchanged.

An example of supervised metric learning is given for an experiment of tactile stimulation in an anesthetized rat forepaw. In this experiment stimuli were applied in 9 sites, while data was obtained from a 32 channel electrode array placed in the somatosensory cortex of the animal. With this information it was possible to train a linear metric projection that maps the data to a lower space so that the labels are as separable as possible.

In conclusion, metric learning provides a useful tool to extract useful information from the high dimensional data to control all degrees of freedom in the lower dimensional space. PCA allows for unsupervised extraction of muscle synergies in the neuromuscular data, both for simple and composite movements. This unsupervised control signals extraction allows the amputee to easily learn to control the prosthesis. Supervised methods to map this high dimensionality are possible but they need labeling. PCA linearity characteristic is not perfect in capturing the variance of the MUAPs; the use of non-linear approaches would lead to better results, taking into account the trade-off between extraction quality and processing power.